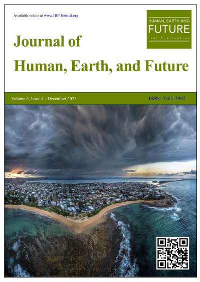
Available online at www.HEFJournal.org

Journal of
Human, Earth, and Future

ISSN: 2785-2997

Vol. 6, No. 4, December, 2025



Estimation Risk Exposure to Nickel and Cobalt in Air Using a Monte Carlo Simulation

Sherly Wulandari [1], Anwar Mallongi [2*], Budimawan [3], Agus Bintara Birawida [4], Nur Nasry Noor [5], Lalu Muhammad Saleh [6]

[1] *Doctoral Program Student, Faculty of Public Health, Hasanuddin University, Makassar, 90245, Indonesia.*

[2] *Department of Environmental Health, Faculty of Public Health, Hasanuddin University, Makassar, 90245, Indonesia.*

[3] *Department of Marine Science, Faculty of Marine Science and Fisheries, Hasanuddin University, Makassar, 90245, Indonesia.*

[4] *Department of Environmental Health, Faculty of Public Health, Hasanuddin University, Makassar, 90245, Indonesia.*

[5] *Department of Epidemiology, Faculty of Public Health, Hasanuddin University, Makassar, 90245, Indonesia.*

[6] *Department of Occupational Safety and Health, Faculty of Public Health, Hasanuddin University, Makassar 90245, Indonesia.*

Received 16 June 2025; Revised 18 October 2025; Accepted 24 October 2025; Published 01 December 2025

Abstract

Exposure to airborne nickel (Ni) and cobalt (Co) poses significant non-carcinogenic health risks, particularly with chronic inhalation. This study quantifies the health risks associated with Ni and Co exposure using a Monte Carlo simulation to incorporate variability and uncertainty in exposure assessment. Air samples were analyzed to determine metal concentrations, and risk characterization was performed through the calculation of Hazard Quotient (HQ) and Target Hazard Quotient (THQ) values based on United States Environmental Protection Agency (USEPA) guidelines. The probabilistic analysis revealed that the mean HQ and THQ values for both Ni and Co exceeded the safe threshold (HQ > 1, THQ > 1), indicating a high probability of health risks across the population, especially among adults. Sensitivity analyses identified inhalation rate, exposure duration, and exposure frequency as the most influential factors, while body weight, average exposure time, and reference concentration (RfC) served as mitigating variables. The results highlight a significant potential for non-carcinogenic effects from Ni and Co inhalation, emphasizing the need for stringent air quality management and targeted public health interventions. This study demonstrates the importance of applying probabilistic risk assessment models to better understand and manage environmental health hazards.

Keywords: Nickel; Cobalt; Health Risk Assessment; Monte Carlo Simulation; Airborne Metals; Environmental Exposure.

1. Introduction

Nickel (Ni) and cobalt (Co) are essential metals that are widely used in various industrial sectors, such as manufacturing, mining, energy production, and the chemical industry [1]. Global demand for these two metals continues to increase in line with their strategic role in the manufacture of stainless steel, electric vehicle batteries, and high-performance metal alloys [2]. This increased demand has driven massive mining and refining activities for nickel and cobalt in various countries, including Indonesia, which has significant nickel reserves.

* Corresponding author: anwar.mallongi@unhas.ac.id

http://dx.doi.org/10.28991/HEF-2025-06-04-03

However, despite their benefits, exposure to Ni and Co, even at low concentrations, can pose serious health risks to humans. Low-level Ni exposure can irritate the respiratory tract, cause mild bronchitis, and, over the long term, increase the risk of chronic lung disorders such as fibrosis and lung cancer [3]. Additionally, Ni is known as a strong allergen that can trigger contact dermatitis and affect immune system responses [4]. Meanwhile, Co exposure is associated with respiratory system disorders, reduced lung function, pulmonary fibrosis, and potential carcinogenic effects [5, 6]. Epidemiological evidence suggests that long-term Co exposure can increase the incidence of certain types of cancer, including colon cancer [7].

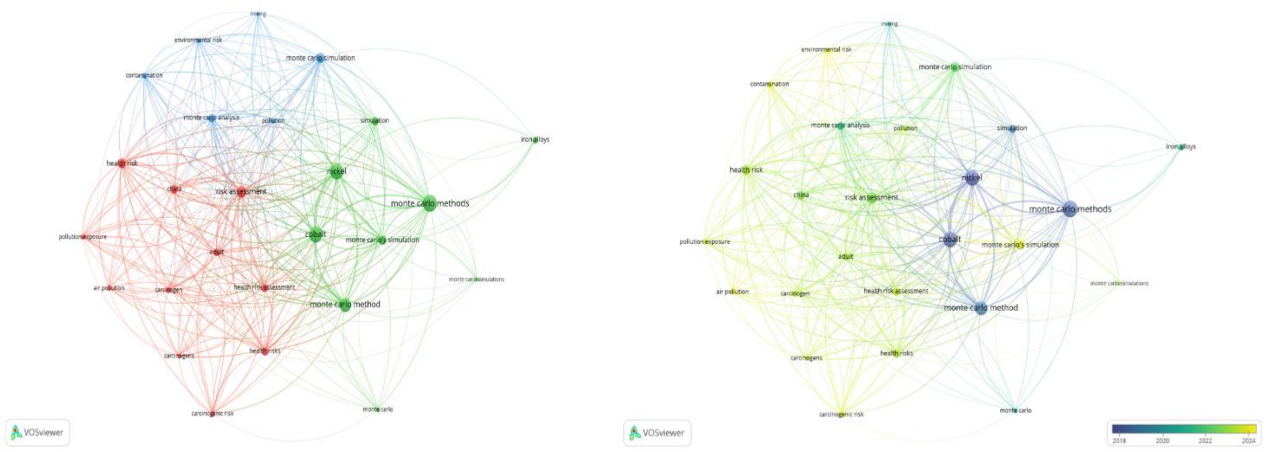
The primary route of exposure to these heavy metals for communities near mines is through inhalation of airborne particles. Particles containing Ni and Co can disperse into the atmosphere, be inhaled, and then be deposited in lung tissue and other organs, potentially causing chronic health effects [8]. Therefore, health risk analysis is crucial to determine the extent to which heavy metal exposure affects communities near mining areas [9]. Human health risk assessment is a systematic process to estimate the nature and likelihood of adverse health effects on humans exposed to environmental contaminants, both currently and in the future [10].

However, the reliability of health risk estimates depends heavily on the quality and completeness of exposure data. In practice, airborne heavy metal concentration data often exhibit high variability and uncertainty due to differences in emission sources, meteorological conditions, and limitations in monitoring coverage [11]. To address this challenge, the Monte Carlo Simulation (MCS) method has emerged as an effective approach for incorporating uncertainty and variability into risk analysis. By simulating thousands of exposure scenarios, MCS can generate probabilistic estimates that provide a more comprehensive picture of health risks [12-14].

Recent research indicates that MCS can enhance the quality of health risk assessments. For example, Sakan et al. [15] applied MCS to assess health risks from exposure to volatile organic compounds in the footwear industry, demonstrating its effectiveness in quantifying uncertainty and determining confidence intervals for hazard indices and cancer risk. Similarly, Paul et al. [16] used MCS to assess exposure to respirable dust in welding processes, reinforcing the effectiveness of this method in supporting occupational health interventions. In Iran, MCS has been applied to analyze the risks of mercury exposure in small-scale gold mining areas, revealing significant health impacts on miners and surrounding communities [17].

However, the use of MCS in assessing health risks from Ni and Co exposure in the air in mining areas remains limited, particularly in Indonesia [18]. Previous studies in Indonesia have generally focused on other heavy metals such as mercury, lead, or arsenic, and have more frequently examined exposure pathways through water and soil rather than air [19, 20]. Additionally, few studies have specifically combined MCS with sensitivity analysis to identify dominant factors influencing risk variability in nickel and cobalt mining areas [21, 22].

Based on Figure 1 this finding is supported by bibliometric mapping results, which show that the keywords “health risk,” “air pollution,” “mercury,” and ‘lead’ form a large, closely interconnected cluster, while the keywords “nickel,” “cobalt,” and “Monte Carlo methods” appear as small nodes separated from the main cluster. This indicates that the application of Monte Carlo-based probabilistic approaches in assessing health risks from exposure to nickel and cobalt in the air has not been widely developed. Therefore, this study aims to address this gap by integrating laboratory measurements of air quality, probabilistic estimates based on Monte Carlo simulations, and sensitivity analysis to identify dominant factors, thereby providing a more comprehensive and evidence-based understanding of public health risks around nickel mining areas.



(a) (b)

Figure 1. (a) Network Visualization and (b) Overlay Visualization of keyword co-occurrence in studies on Nickel, Cobalt, health risks, Monte Carlo Simulation, and Air

2. Materials and Methods

2.1. Area of Study

Sorowako is one of the areas in East Luwu Regency, South Sulawesi Province, Indonesia, with an area of approximately 808.27 km². This area has a tropical climate with an average annual rainfall of 258 mm, and the number of rainy days reaches approximately 216 days per year. The average air temperature ranges from 22–30°C, with relative humidity reaching 62–96%. One of the main geographical features of Sorowako is the presence of Lake Matano, the deepest freshwater lake in Southeast Asia [23]. This sub-district includes several villages and sub-districts, such as Sorowako Village, Nikkel Village, Magani Village, Nuha Village, and Matano Village. In addition, Sorowako is known as a center for mining industry activities, especially Ni, which is the main economic sector of this region [24]. This research focused on Sorowako Village, Nikkel Village, and Magani Village, which are the main locations for nickel mining activities (Figure 2).

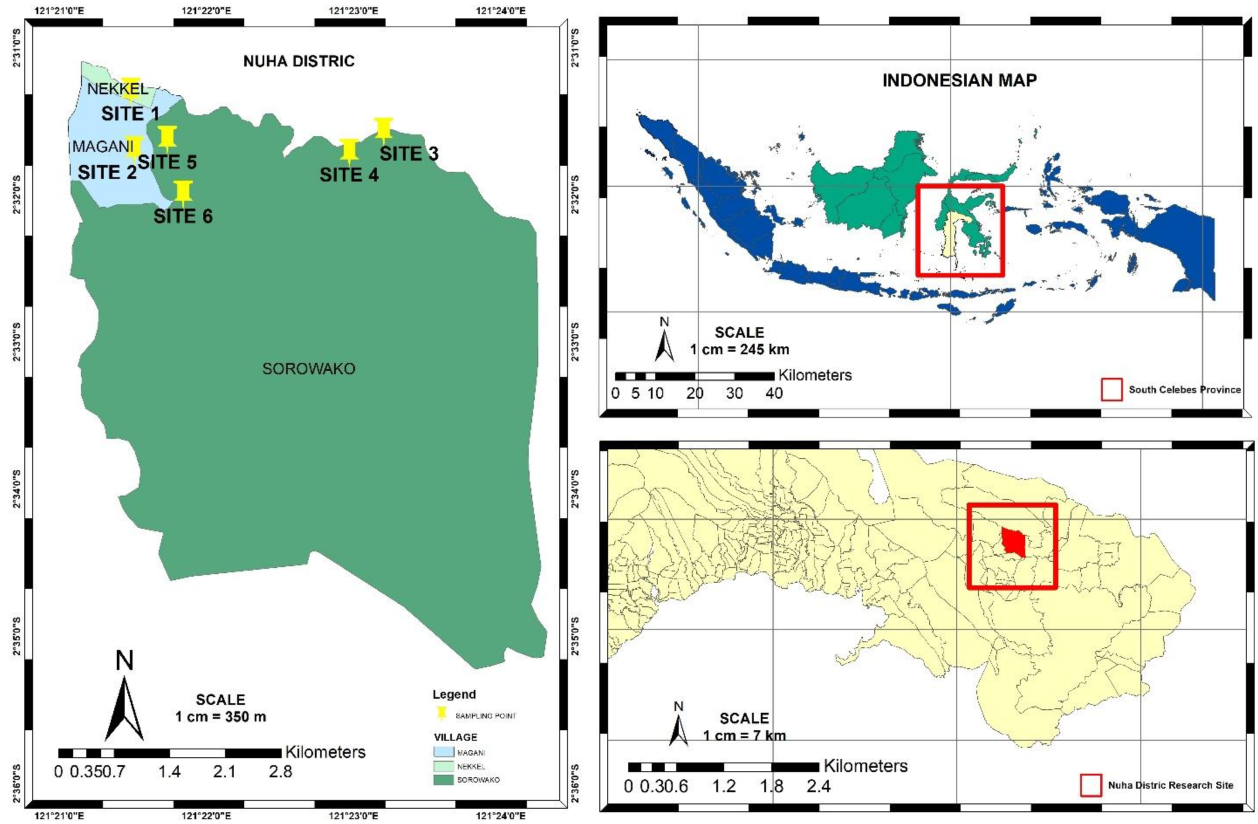


Figure 2. Sampling locations and research areas

2.2. Study Design

This research is grounded in the risk assessment framework as outlined by the U.S. Environmental Protection Agency (USEPA), which consists of four key components: hazard identification, dose-response assessment, exposure assessment, and risk characterization. Specifically, the study employs a probabilistic approach using Monte Carlo simulation (MCS) to estimate non-carcinogenic health risks arising from inhalation exposure to airborne nickel and cobalt [25]. The theoretical basis for using Monte Carlo simulation lies in its capacity to model the inherent uncertainty and variability in environmental exposure parameters such as inhalation rate, exposure duration, and concentration levels by treating them as probability distributions rather than fixed values. This probabilistic modeling approach is rooted in quantitative risk assessment theory, which emphasizes the importance of characterizing the full range and likelihood of possible health outcomes rather than relying solely on point estimates [26].

The estimation of health risk uses the Hazard Quotient (HQ) and Target Hazard Quotient (THQ) models, which compare the estimated exposure dose to established reference doses (RfD). When HQ or THQ values exceed 1, they indicate potential for adverse health effects. In this study, MCS is used to analyze potential risks in depth by evaluating the impact of uncertain variables and identifying possible different outcomes. This simulation will be run with the help of Oracle Crystal Ball software version 11.1.2 as an add-in in Microsoft Excel 2018. By integrating Monte Carlo simulation into these calculations, the research provides a more comprehensive and realistic characterization of risk, aligning with the theory of environmental health risk modeling that advocates probabilistic frameworks for more informed decision-making under uncertainty [27].

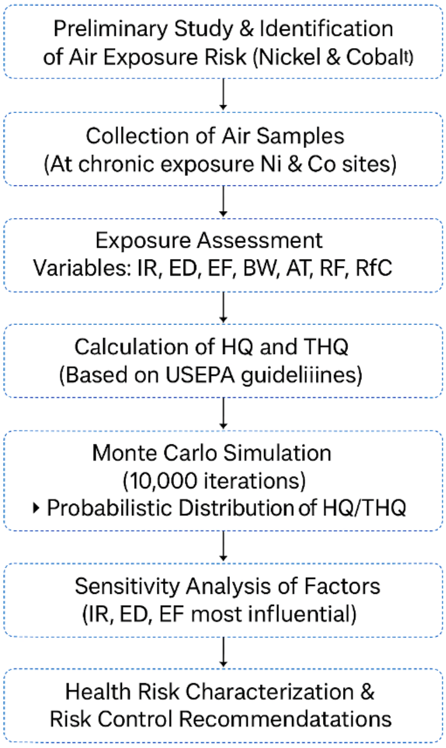


Figure 3. A Flowchart Study

2.3. Sampling Technique

Air sampling was conducted at six points spread across Sorowako Village, Nikkel Village, and Magani Sub-district, with the following distribution: four points in Sorowako Village, one point in Nikkel Village, and one point in Magani Sub-district. Each air sample measured included five respondents living in the area of the measurement point. Air sampling was conducted using a High-Volume Air Sampler (HVAS) to capture suspended particles. Air samples were collected for 24 hours in stable weather conditions to avoid variations due to rain or atmospheric changes, National Standardization Agency. Furthermore, it was analyzed using the Atomic Absorption Spectrometry (AAS) method in a laboratory that has met the SNI 7119-4:2017 standard.

The population of this study included residents domiciled in Sorowako Village, Nikkel Village, and Magani Village, located within a radius of 4–5 km from the mining area. Inclusion Criteria in this study are: Aged 36–60 years, have lived in the research location for > 5 years, have no history of work in the mining/heavy metal industry (to avoid bias due to direct exposure in the workplace). Exclusion Criteria: Sufferers of chronic kidney or liver disease (because these organs play a role in heavy metal metabolism), Individuals with a history of work in the mining industry sector for more than 1 year (to distinguish environmental exposure from occupational exposure. The total sample obtained was 294 respondents, with details of 99 respondents from Sorowako Village, 98 respondents from Nikkel Village, and 97 respondents from Magani Village. Blood sampling was carried out by purposive sampling from individuals at each location to ensure representation of the population at risk of exposure to heavy metals Ni and Co.

The selection of 5 respondents per air sampling point was based on logistical constraints, ethical considerations, and the design of the exposure assessment framework, which focused on representing a range of demographic characteristics (e.g., age, body weight, activity level) within each microenvironmental setting. Our primary aim was to integrate site-specific air quality data with individual-level exposure scenarios, rather than to conduct large-scale epidemiological surveys. The health risk assessment relied primarily on environmental concentration data, which were then combined with individual exposure factors through Monte Carlo simulations to generate a robust probabilistic distribution of risk across the population. This modeling approach compensates for the limited number of respondents by simulating thousands of possible exposure scenarios, thereby enhancing statistical validity and generalizability.

Data in this study were collected through a questionnaire to obtain information related to demographic characteristics, health history, environmental exposure, and behaviors and habits that affect exposure to heavy metals Ni and Co. Demographic information includes age, gender, and occupation, while health history includes diseases or symptoms related to heavy metal exposure. Environmental exposure includes location of residence, distance from pollution sources, and duration of residence, while behavior includes habits such as smoking and consumption of potentially contaminated water.

2.4. Data Analysis

Airborne concentrations of nickel (Ni) and cobalt (Co) were collected from multiple sampling sites surrounding the Sorowako nickel mining area, utilizing high-volume air samplers to capture representative exposure scenarios. Metal concentrations were quantified using inductively coupled plasma mass spectrometry (ICP-MS) and subsequently analyzed to estimate the non-carcinogenic health risks [28, 29]. The exposure assessment incorporated key variables such as inhalation rate, exposure time, exposure frequency, duration, body weight, and reference concentrations, following United States Environmental Protection Agency (USEPA) guidelines [30].

Hazard Quotient (HQ) is used as a general non-carcinogenic risk metric that compares the estimated exposure concentration to a reference concentration (RfC) derived from chronic inhalation toxicity data. It is calculated as the ratio of the average daily intake of a contaminant to its corresponding RfC. HQ values above 1 indicate potential non-carcinogenic health risks. Target Hazard Quotient (THQ), originally developed by the U.S. EPA for assessing health risks from trace elements in food, is conceptually similar to HQ but incorporates specific exposure parameters (e.g., body weight, exposure frequency, duration, and averaging time) in a more detailed and structured manner. In this study, THQ is adapted for inhalation exposure to quantify the individual element-specific risk contribution, enabling a refined probabilistic interpretation when combined with Monte Carlo simulations.

A Monte Carlo simulation with 10,000 iterations was employed to model the probabilistic distribution of Hazard Quotient (HQ) and Target Hazard Quotient (THQ) values, capturing variability and uncertainty in the risk parameters [31]. We selected 10,000 iterations for the Monte Carlo simulation based on established practices in environmental health risk assessment literature, where this number is commonly used to ensure a balance between computational efficiency and result stability. Several published studies (e.g., USEPA risk assessments and peer-reviewed environmental exposure analyses) have demonstrated that 10,000 iterations generally provide sufficient sampling of parameter distributions to produce stable and representative output distributions for health risk metrics such as HQ and THQ [32]. Toxicological parameters, including Reference Dose (RfD) for Ni and Co, were obtained from the US-EPA Integrated Risk Information System (IRIS) database. Non-carcinogenic health risks were calculated using the Hazard Quotient (HQ) and target hazard quotient (THQ) approaches, which are the comparison between Chronic Daily Intake (CDI) and RfD. CDI is calculated based on heavy metal concentration, inhalation rate or ingestion rate, exposure frequency, exposure duration, body weight, and average exposure time, by US-EPA guidelines. The basic formula used is [33];

$$\mathrm{CDI} = \frac{\mathrm{C} \times \mathrm{IR} \times \mathrm{EF} \times \mathrm{ED}}{\mathrm{WB} \times \mathrm{AT}} \tag{1}$$

where, CDI is Chronic Daily Intake ($\mu g/m^3$/day); IR is Inhalation rate; EF is Frequency of Exposure (Day/year); Dt is Duration of Exposure (Year); C is Concentration (mg/kg); and WB is Body Weight (kg).

$$HQ = \frac{CDI}{RfD} \tag{2}$$

where, HQ is Hazard quotient ($\mu g/m^3$/day); and RfD is Reference of Dose ($\mu g/m^3$/day).

$$\mathrm{THQ} = \frac{\mathrm{fE} \times \mathrm{Dt} \times \mathrm{R} \times \mathrm{C}}{\mathrm{RfD} \times \mathrm{WB} \times \mathrm{AT}}\ 10^{-3} \tag{3}$$

where, THQ is Target Hazard Quotient ($\mu g/m^3$/day); fE is Frequency of Exposure (Day/year); Dt is Duration of Exposure (Year); R is Inhalation Rate (kg/hour); C is Concentration (mg/kg); RfD is References of Dose (mg/kg); WB is Body Weight (kg); and AT is Time Average (Day/year).

The simulation results demonstrated that both Ni and Co exhibited mean HQ and THQ values significantly exceeding the threshold value of 1, indicating considerable health risks for the exposed population, especially among sensitive subgroups such as adults. Sensitivity analysis revealed that inhalation rate, exposure duration, and exposure frequency were the most influential factors contributing to risk, while higher body weight, longer averaging time, and higher reference concentration values acted as mitigating elements [34]. The findings highlighted the importance of targeted air quality interventions around the mining area to reduce exposure levels. Additionally, the application of probabilistic modeling through Monte Carlo simulation proved effective in providing a comprehensive and realistic estimation of health risks under environmental uncertainty conditions [35].

Sensitivity analysis was conducted to identify the input parameters that contributed most to the variation in HQ results. The Ranked Pearson Correlation Coefficient (PCC) and Standardized Regression Coefficient (SRC) methods were used to evaluate sensitivity, with the results visualized in the form of tornado diagrams. Through this analysis, parameters such as heavy metal concentration, ingestion rate, and body weight were identified as dominant factors influencing risk. In addition, statistical tests were conducted to support the data analysis. The Shapiro-Wilk normality test was used to determine the distribution of the data the results of the analysis are presented with 95% confidence intervals, both for HQ, THQ values and Monte Carlo simulation results, to increase the reliability of the interpretation of the research results.

3. Results

Based on Table 1, the sociodemographic characteristics of the respondents in this study provide an overview of the population living around the mining area. Most respondents are in the 41–50 age range, which dominates in almost all locations (40–51.5%). Meanwhile, the proportion of respondents over the age of 51 is lower, ranging from 13% to 33%, reflecting a relatively good distribution of productive ages among the population.

In terms of gender, women are more dominant in some locations, particularly at Site I (80%) and Site IV (58.3%), while men are more numerous in other locations, such as Site V (59.2%) and Site VI (52.6%). These differences likely reflect the division of roles in household activities, the environment, and formal and informal work in each area.

All respondents had a minimum education level of high school/vocational school (ranging from 55.7% to 88%), indicating fairly good access to education. A small proportion of respondents had pursued higher education, with bachelor's degree holders accounting for 12.4% at Site VI, although no respondents held master's degrees. This suggests that the majority of respondents have sufficient educational backgrounds to understand environmental and basic health issues.

Regarding length of residence, respondents at all locations had lived in the area for a considerable period, with most reporting over 20 years of residence. This relatively long duration of residence indicates a high level of cumulative exposure to environmental conditions, including emissions from mining activities.

The distance from homes to mining sites is divided into two ranges, 4.00–4.79 km and 4.80–5.63 km, depending on the location, with respondents at each site consistently falling within these distance ranges.

For drinking water sources, most respondents used bottled water, particularly at Site VI (68.0%) and Site II (92%), while others still relied on the Regional Water Supply Company (PDAM) (60–60.2%). No respondents reported using dug wells, boreholes, rivers, or lakes as drinking water sources. Meanwhile, for bathing purposes, all respondents (100%) at all locations rely on PDAM, indicating relatively good access to clean water across the entire study area.

Table 1. Sociodemographic characteristics of respondents (n=294) based on sampling location

Variable	Category	Total / Site						Percentage (%) / Site					
		I	II	III	IV		VI	I	II	III	IV	V	VI
Age (Years)	35-40	8	5	7	8		39	32	20	28	33.3	39.8	40.2
	41-50		15	12	8		50	40	60	48	33.3	50	51.5
	>51	7	5	6	8	10	8	28	20	24	33.3	10.2	8.2
Gender	Male	5	15	12	10	58	49	20	60	48	41.7	59.2	50.5
	Female		10	13	14	40	48	80	40	52	58.3	40.8	49.5
Education	Junior High School	1	3	4	2	25	24	4	12	16	8.3	25.5	24.7
	Senior High School		15	16	20	60	54	88	60	64	83.3	61.2	55.7
	Diploma	0	0	0	0	7	4	0	0	0	0	7.1	4.1
	Bachelor's Degree	1	5	4	2	6	12	4	20	16	8.3	6.1	12.4
	Master's Degree	1	2	1	0	0	3	4	8	4	0	0	3.1
Work	Formal	1	4	5	8	33	36	4	16	20	33.3	33.7	37.1
	Informal	4	10	12	6	49	24	16	40	48	25	50	24.7
	Housewife		11	8	10	16	37	80	44	32	41.7	16.3	38.1
Drinking Water Source	Local water company		2	3	4	59	31	60	8	12	16.7	60.2	32
	Refill water		23	22	20	39	66	40	23	22	20	39	66
Bathing Water Source	Local water company		25	25	24	98	97	100	100	100	100	100	100
	Refill water	0	0	0	0	0	0	0	0	0	0	0	0

Based on Table 2, Ni concentrations ranged from 0.0439 µg/m³ to 0.3889 µg/m³, with an average of 0.1396 µg/m³. Meanwhile, cobalt (Co) concentrations range from 0.0002 µg/m³ to 0.0007 µg/m³, with an average of 0.000383 µg/m³. The highest concentrations for both metals were detected at Site V, while the lowest concentrations were recorded at Site I. According to the World Health Organization (WHO), the recommended annual average limit for nickel in ambient air is 0.0025 µg/m³, primarily based on carcinogenic risk considerations. The US Environmental Protection Agency (USEPA) has also established a reference concentration (RfC) for chronic inhalation exposure to nickel compounds of 0.02 µg/m³. In this study, nickel concentrations at all locations significantly exceeded WHO guidelines, with Location V recording the highest exceedance at 0.3889 µg/m³, nearly 155 times the WHO recommended limit.

Although cobalt concentrations were much lower (ranging from 0.0002 to 0.0007 µg/m³), there are no official WHO air quality standards for cobalt. However, based on toxicological evidence, cobalt concentrations in air above 0.0001 mg/m³ (100 ng/m³) may pose respiratory risks. The cobalt levels recorded in this study remain below this threshold. These findings highlight that nickel exposure is a more critical health concern in the Sorowako region, suggesting the need for local mitigation efforts to reduce nickel levels in the air.

Table 2. Ni and Co concentrations in the air based on sampling location

Site	Concentration (µg/m³)		Temperature (°C)	Humidity (%)	Coordinate Point	
	Ni	Co			Latitude	Longitude
I	0.1182	0.0004	33.7	56.4	2°31'38''	121°21'44''
II	0.0752	0.0004	31.5	61.8	2°32'0''	121°21'51''
III	0.0785	0.0003	33.4	55.4	2°31'34''	121°23'12''
IV	0.0439	0.0002	31.5	55.4	2°31'44''	121°22'58''
V	0.3889	0.0007	33.6	50.6	2°31'43''	121°21'31''
VI	0.1330	0.0003	32.2	50.9	2°31'18''	121°21'29''

Based on Figure 4 shows that the probabilistic distribution of the Hazard Quotient (HQ) for nickel in these respondents shows that the average HQ value is > 1, which is above the safe limit according to the reference concentration (RfC). Most of the simulation values are above HQ > 1, with the 10th percentile being 8 and the 90th percentile being 16, indicating that 90% of the population has a very high risk, while the other 5% has a high risk. This log-normal distribution shows significant variability due to factors such as nickel concentration, exposure patterns, and individual weight. The average value is above the safe limit; individuals with HQ above 1 have the potential for non-carcinogenic health risks, especially in chronic exposure.

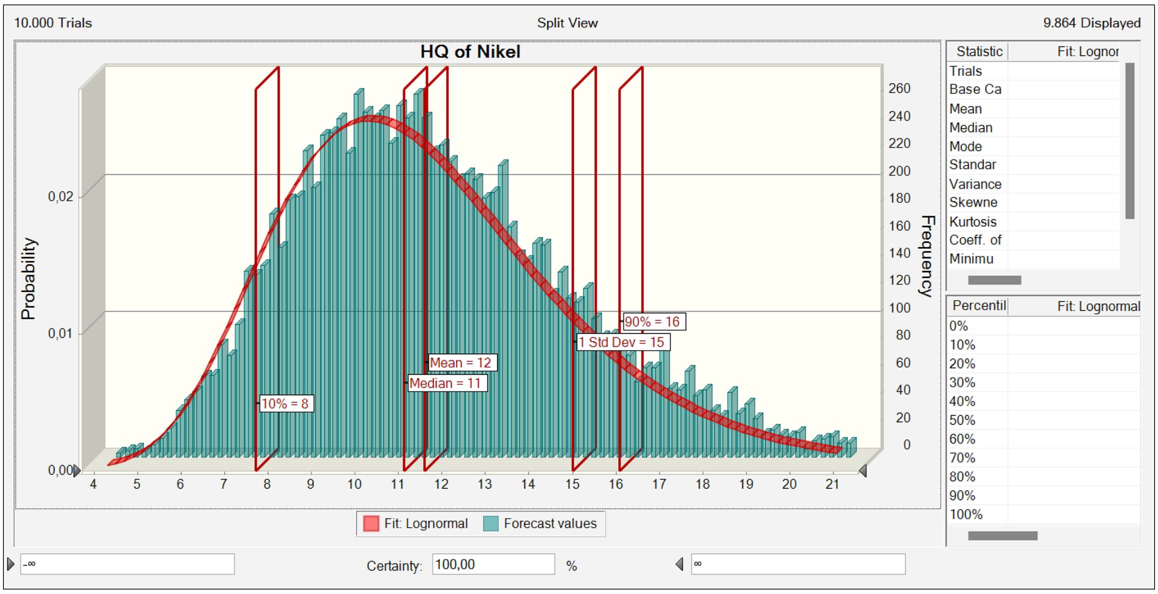


Figure 4. Probabilistic distribution of nickel hazard quotient (HQ)

Based on Figure 5 shows how much each factor affects the level of health risk due to cobalt exposure in respondents. The most influential factor is the duration of exposure in years (ED) at 13.7%, followed by the nickel concentration factor in the air (C) at 12.5%, then followed by the amount of nickel inhaled (Inhalation Rate) at 12.3%, then the frequency of exposure (EF) at 12.1% and the length of exposure time per day (ET) at 11.9%. However, other factors such as the average exposure time (AT) factor showed a negative effect of -13.0%, followed by the reference of concentration (RfC) factor at -12.6% and the body weight (BW) factor at -11.9%. The three negative factors indicate that the higher the average exposure time (AT), reference concentration (RfC), and body weight (BW), the smaller the health risk due to cobalt exposure. This is because the greater average exposure time (AT), reference of concentration (RfC), and body weight (BW) cause the dose of nickel entering humans per kilogram to be smaller, so that its impact on health decreases. The negative effects of the average exposure time (AT), reference of concentration (RfC), and body weight (BW) are natural mitigation factors that help reduce the level of risk.

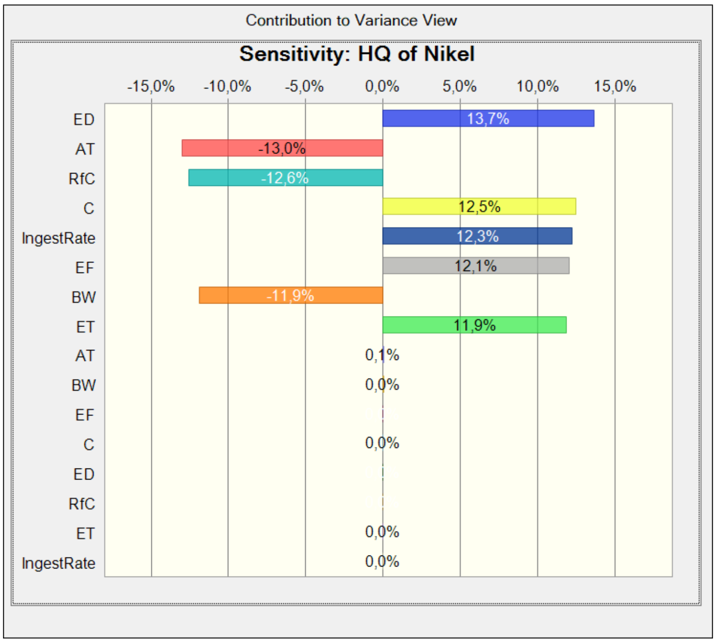


Figure 5. Nickel sensitivity hazard quotient (HQ)

Based on Figure 6 shows that the probabilistic distribution of the Target Hazard Quotient (THQ) for nickel in these respondents shows that the average THQ value is > 1, which exceeds the safe limit according to the reference concentration (RfC). Most of the simulated values are above THQ > 1, with the 5th percentile being 7.68 and the 95th percentile being 19.52, indicating that 95% of the population has high risk, while the other 5% has moderate risk. This log-normal distribution shows significant variability due to factors such as nickel concentration, exposure patterns, and individual weight. Although the average value is above the safe limit, individuals with THQ > 1 have potential non-carcinogenic health risks, especially in chronic exposure.

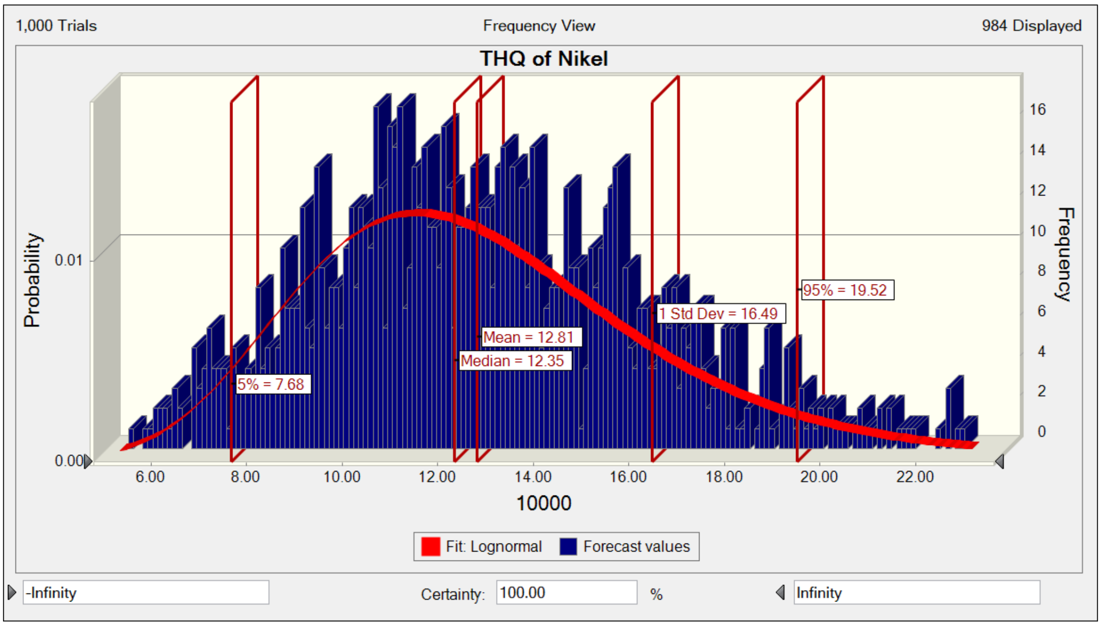


Figure 6. Probabilistic target hazard quotient (THQ) Nickel

Based on Figure 7 shows how much each factor affects the level of health risk due to nickel exposure in respondents. The most influential factor is the frequency of exposure in daily/year (EF) factor of 15.0%, followed by the duration of exposure in years (ED) factor of 14.3%, then the nickel concentration factor in the air (C) factor of 12.5%, then the duration of exposure per day (ET) factor of 10.1% and the inhaled nickel concentration factor (Inhalation Rate) of 10.0%. However, other factors show a negative influence, such as the reference of concentration (RfC) factor of -14.2%, followed by the body weight factor (BW) of -13.5% and the average exposure time factor (AT) of -10.4%. The three factors that have a negative influence indicate that the higher the reference of concentration (RfC), body weight (BW), and average exposure time (AT), the smaller the health risk due to nickel exposure. This happens because the larger reference concentration (RfC), body weight (BW), and average exposure time (AT) cause the dose of nickel entering humans per kilogram to be smaller, so that its impact on health decreases. The negative influence of reference concentration (RfC), body weight (BW), and average exposure time (AT) is a natural mitigation factor that helps reduce the level of risk.

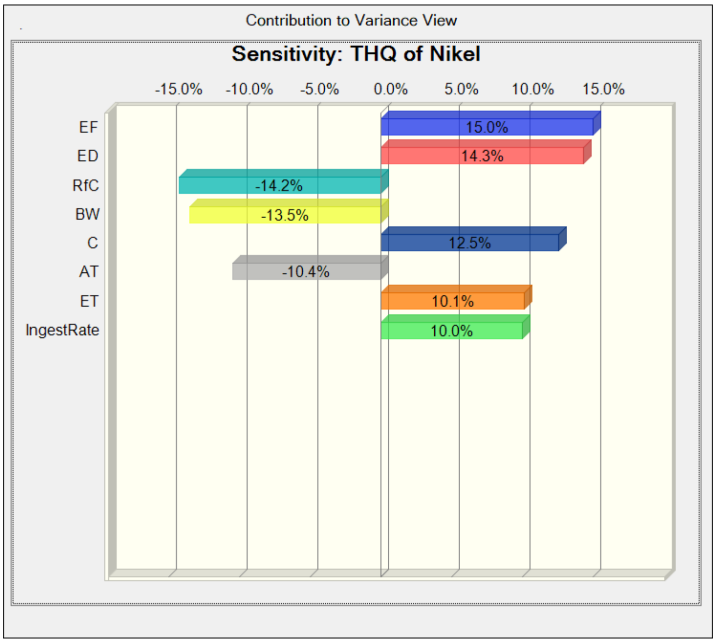


Figure 7. Nickel sensitivity hazard quotient (HQ)

Based on Figure 8 shows that the probabilistic distribution of the Hazard Quotient (HQ) for cobalt in these respondents shows that the average HQ value is > 1, which is above the safe limit according to the reference concentration (RfC). Most of the simulation values are above HQ > 1, with the 5th percentile being 7 and the 95th percentile being 18, indicating that 95% of the population has a very high risk, while the other 5% has a high risk. This log-normal distribution shows significant variability due to factors such as cobalt concentration, exposure patterns, and individual weight. The average value is above the safe limit; individuals with HQ above 1 have the potential for non-carcinogenic health risks, especially in chronic exposure.

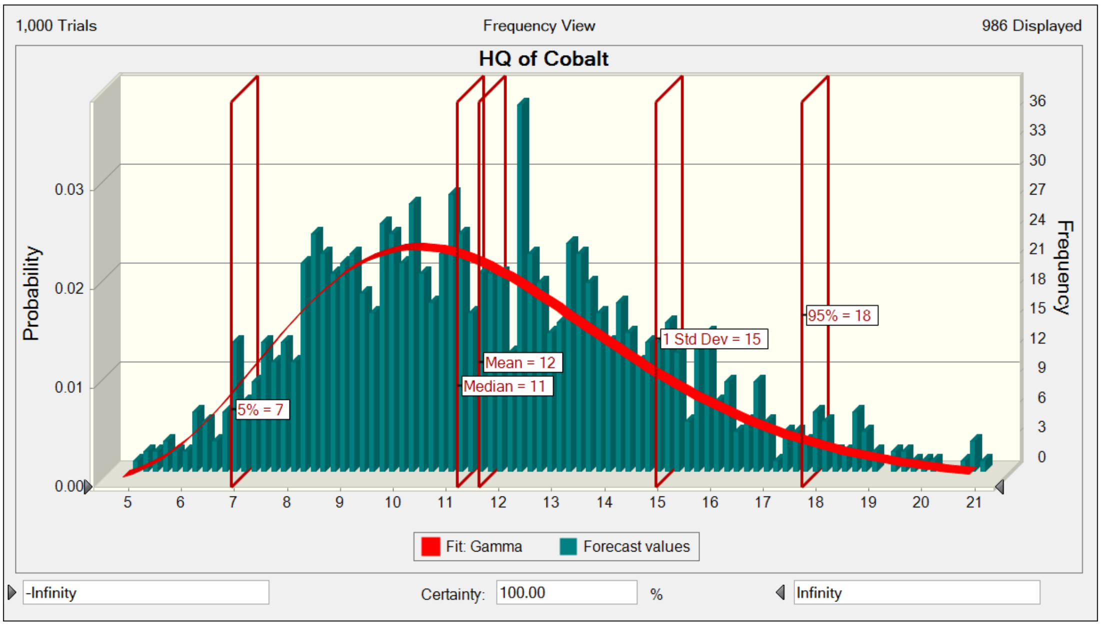


Figure 8. Cobalt hazard quotient (HQ) probability

Based on Figure 9 shows how much each factor affects the level of health risk due to cobalt exposure in respondents. The most influential factor is the amount of cobalt inhaled (Inhalation Rate) at 14.7%, followed by the length of exposure time per day (ET) at 13.5%, then the duration of exposure in years (ED) at 13.0%, the frequency of exposure (EF) at 10.3% and the cobalt concentration factor in the air (C) at 9.9%. However, the reference concentration (RfC) factor showed a negative effect of -15.9%, followed by the body weight (BW) factor at -13.1% and the average exposure time (AT) factor at 9.6%. The three factors that had a negative effect indicate that the higher the reference of concentration (RfC), body weight (BW), and average exposure time (AT), the smaller the health risk due to cobalt exposure. This is because the larger reference concentration (RfC), body weight (BW), and average exposure time (AT) cause the dose of cobalt that enters per kilogram to humans to be smaller, so that its impact on health decreases. The negative effects of the reference of consentation (RfC), body weight (BW), and average exposure time (AT) are natural mitigation factors that help reduce the level of risk.

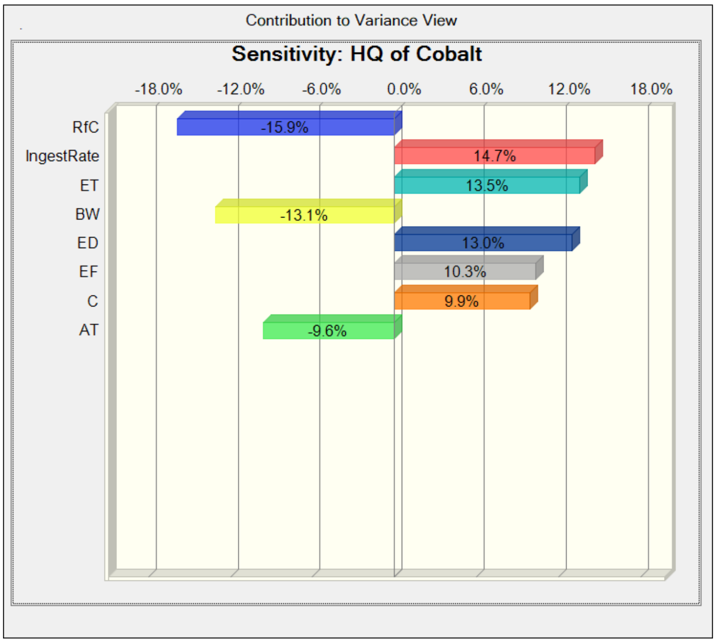


Figure 9. Sensitivity hazard quotient (HQ) Cobalt

Based on Figure 10 shows that the probabilistic distribution of the Target Hazard Quotient (THQ) for cobalt in these adults shows that the average THQ value is > 1, which exceeds the safe limit according to the reference of concentration (RfC). Most of the simulated values are above THQ > 1, with the 5th percentile being 3.51 and the 95th percentile being 9.05, indicating that 95% of the population is high, while the other 5% is at moderate risk. This log-normal distribution shows significant variability due to factors such as cobalt concentration, exposure patterns, and individual weight. Although the average value is above the safe limit, individuals with THQ > 1 have potential non-carcinogenic health risks, especially in chronic exposure.

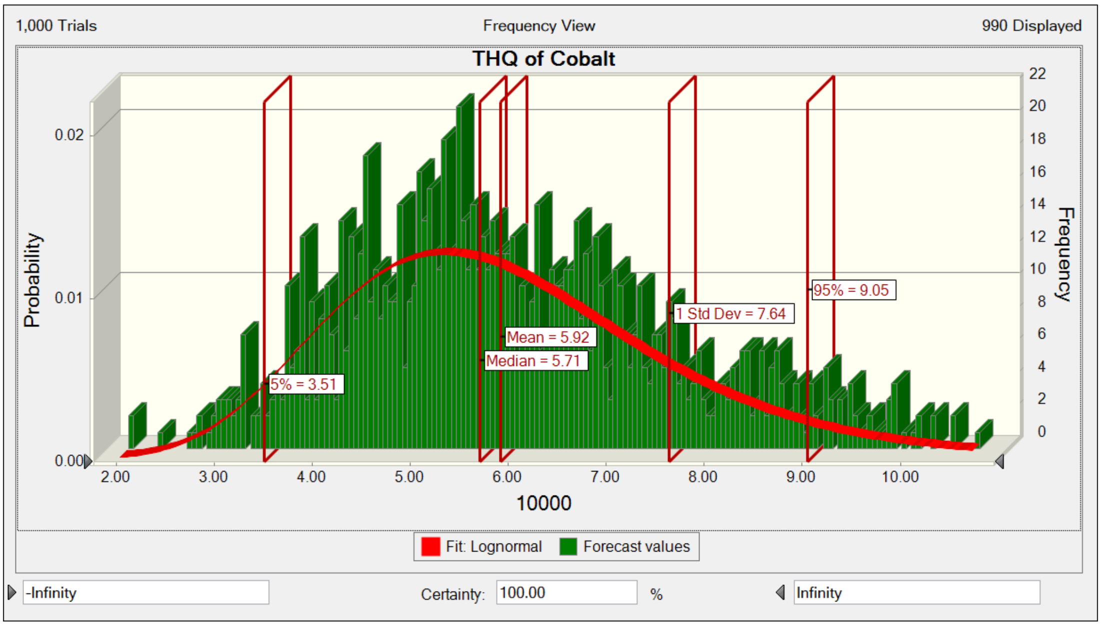


Figure 10. Probabilistic distribution of the Cobalt target hazard quotient (THQ)

Based on Figure 11 shows how much each factor affects the level of health risk due to cobalt exposure in respondents. The most influential factors are the length of exposure time per day (ET) factor of 14.6%, the duration of exposure in years (ED) factor of 13.7%, followed by the cobalt concentration factor in the air (C) factor of 12.5%, then followed by the amount of cobalt inhaled (Inhalation Rate) factor of 12.3%, then the frequency of exposure factor (EF) of 12.1% and the length of exposure time per day (ET) factor of 11.9%. However, other factors such as the average exposure time factor (AT) showed a negative effect of -13.0%, followed by the reference of concentration (RfC) factor of -12.6% and the body weight factor (BW) of -11.9%. The three factors that have a negative influence indicate that the higher the average exposure time (AT), reference of concentration (RfC), and body weight (BW), the smaller the health risk due to cobalt exposure. This occurs because the greater average exposure time (AT), reference of concentration (RfC), and body weight (BW) cause the dose of nickel that enters humans per kilogram to be smaller, so that its impact on health decreases. The negative influence of the average exposure time (AT), reference of concentration (RfC), and body weight (BW) is a natural mitigation factor that helps reduce the level of risk.

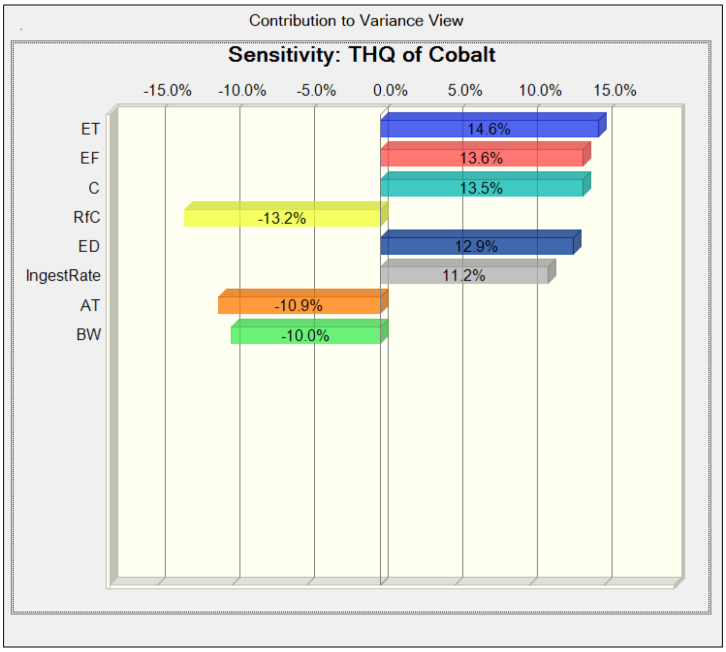


Figure 11. Cobalt sensitivity hazard quotient (HQ)

4. Results

Intensive nickel mining activities in Indonesia, especially with open pit mining systems, produce emissions of heavy metal particles such as nickel (Ni) and cobalt (Co) that are spread into the environment [36]. Residential areas within the contamination radius are the main locations for atmospheric deposition of these metals. Accumulation of heavy metals through the air can have direct implications for public health through inhalation [37]. Assessment of health risks due to exposure to heavy metals such as nickel and cobalt is a central issue in environmental toxicology studies. The probabilistic approach through the Hazard Quotient (HQ) and Target Hazard Quotient (THQ) provides a quantitative picture of the potential non-carcinogenic risks that arise in exposed populations [38]. This study found that the HQ and THQ values for both metals were above the safe threshold value (HQ/THQ> 1), indicating a significant health risk.

Cobalt HQ showed a log-normal distribution with a mean value > 1 and a range between the 5th and 95th percentiles ranging from 7 to 18. This indicates that a large portion of the population has exposure that has the potential to cause long-term health impacts. A study by Soltanpour et al. [39] confirmed that chronic cobalt exposure can affect the respiratory and cardiovascular systems. Sensitivity analysis showed that the inhalation factor (Inhalation Rate) was the most significant component affecting the HQ value, followed by the duration and frequency of exposure. This is in line with the USEPA model, which emphasizes the importance of exposure parameters in risk assessment [1].

A based study by Zhao et al. [7] focused on airborne cobalt exposure in communities surrounding battery recycling sites and reported a similarly elevated risk, particularly among informal workers and adults. Their findings confirmed that Co exposure results in HQ values well above the acceptable threshold, further supporting the conclusions of our study. Notably, their sensitivity analysis revealed exposure duration and frequency as the most influential variables, coinciding with our own identification of inhalation rate, exposure frequency, and duration as key risk drivers.

On the other hand, mitigating factors such as Reference Concentration (RfC), body weight (BW), and average exposure time (AT) showed a negative effect on the HQ value. The higher these values, the lower the health risk due to the lower dose distribution per kilogram of body weight. In nickel, the HQ distribution pattern is also log-normal, with values between the 10th and 90th percentiles ranging from 8 to 16. This indicates a high risk experienced by more than 90% of the exposed population, a result consistent with the findings of Sirinara et al. [40] regarding the systemic toxicity of nickel. In the nickel HQ simulation, exposure duration (ED) was the dominant factor (13.7%), followed by nickel concentration in the air (C, 12.5%), inhalation rate (12.3%), and exposure frequency (12.1%). Similar to cobalt, mitigating factors such as AT, RfC, and BW reduced the risk by reducing the dose per kilogram of body weight.

The HQ sensitivity analysis for nickel shows the dominance of annual exposure duration and nickel concentration in the air as the main determinants. These values indicate that the duration and intensity of exposure greatly influence the increase in risk. Cobalt also shows potential risk in adults based on the THQ analysis, where the average value is > 1 with a range of 5th to 95th percentiles ranging from 3.51 to 9.05. Adults are physiologically more vulnerable because they have higher outdoor activities [4, 5]. The sensitivity analysis for cobalt THQ in adults shows that the duration of daily and annual exposure times contributes the most to risk. This shows the importance of controlling exposure time in adults in the context of mitigation. Nickel THQ also shows worrying results, with 95% of the population showing values above the safe threshold, indicating a high health risk, especially for vulnerable groups such as adults and the elderly.

For nickel THQ, the greatest sensitivity came from exposure frequency and air concentration, suggesting that controlling emission sources could be an effective measure to reduce risk. The distribution of THQ for nickel had a similar pattern, with the 5th percentile value being 7.68 and the 95th percentile being 19.52. These values are very high, indicating that even at the lowest simulation, adults are still at risk well beyond the safe threshold. The toxicological mechanisms of cobalt involve enzyme inhibition and the production of reactive oxygen species (ROS), which can cause chronic cell and tissue damage [41]. Nickel is known to cause contact dermatitis and is immunotoxic, in addition to having cumulative effects in the pulmonary system, especially with long-term exposure [23, 24].

A study by Zhang et al. [26] in urban-industrial regions of China, which applied a probabilistic risk assessment framework, also identified Ni as a key contributor to non-carcinogenic health risks, particularly through PM2.5-bound particles. Although their study did not include cobalt, their findings parallel those of the current research, demonstrating HQ values of Ni > 1 and emphasizing the vulnerability of adults due to higher inhalation rates and exposure sensitivity.

This study uses the Monte Carlo simulation method to estimate the variability and uncertainty in risk parameters, according to international standards in quantitative risk assessment [34, 35]. High HQ and THQ values require serious attention, especially in areas with intensive mining or metal industry activities. Environmental regulations should be strengthened with an evidence-based approach like this. Policy recommendations can include controlling heavy metal emission sources, using personal protective equipment (PPE) for industrial workers, and educating the public about the potential dangers of heavy metals [27].

The study conducted in Morowali by Tunggala et al. [8] is very relevant, where they analyzed the environmental impacts caused by mining activities. The findings indicate that these activities imply the risk of hazardous materials being produced. Therefore, Monte Carlo simulation can be an effective tool in calculating the risks and impacts on local biota and the quality of life of the surrounding community. The results of the simulation will provide decision makers with the data needed to formulate better environmental protection [42, 43].

The main uncertainties in the simulation come from fluctuations in metal concentrations in the air, variations in exposure time per individual, and uneven local body weight data. However, by using a probabilistic distribution, the Monte Carlo approach can accommodate this variability and provide more robust estimates. Unlike deterministic approaches, Monte Carlo simulations provide information about the risk range (rather than just a single number), and allow for the calculation of percentiles (e.g., populations with HQ > 1). This is very important in public health planning and evidence-based policy making [44].

With the finding that most of the HQ and THQ simulations showed values > 1, it can be concluded that settlements around the mine are in a high-risk zone. This supports the need for buffer zone policies, limited relocation, or increased air filtration systems in vulnerable settlements. Mitigation strategies can be directed at the most sensitive factors, such as reducing air concentrations (through dust control), reducing the duration and frequency of exposure, and educating the community about safe times to do outdoor activities. Planting protective vegetation can also reduce direct exposure [35].

Further corroboration is provided by Hao et al. [45], who conducted a risk assessment in mining-impacted communities and evaluated multiple metalloids, including Ni and Co. They reported HQ and THQ values above 1 for both metals, and their results emphasized adults' greater vulnerability due to physiological and behavioral factors. Like our study, they utilized a Monte Carlo-based approach to accommodate exposure uncertainty and identified inhalation rate, body weight, and reference concentration (RfC) as dominant contributors to risk variability.

This study also opens up opportunities for the development of AI-based predictive models and spatial data for risk mapping in various geographic locations and different populations. In addition, longitudinal research is needed to observe the real impact of heavy metal exposure on public health over a longer period [46]. This study contributes to the global framework on environmental health, particularly in meeting the Sustainable Development Goals (SDGs), especially in the aspects of clean water, clean air, and protection from hazardous chemicals [41]. The application of quantitative methods in this study strengthens scientific arguments in determining exposure limits and formulating local and international regulations. With the increasing understanding of the risks of heavy metal exposure, multidisciplinary collaboration between toxicologists, epidemiologists, and public policy experts is important in formulating integrated responses to environmental health challenges [30].

5. Conclusion

This study offers a detailed probabilistic estimation of non-carcinogenic health risks resulting from airborne nickel and cobalt exposure in the Sorowako nickel mining area. Utilizing a Monte Carlo simulation, the analysis demonstrated that the average Hazard Quotient (HQ) and Target Hazard Quotient (THQ) for both metals exceeded the safety threshold of 1, signaling a potentially significant health risk to the local population. Adults were identified as particularly vulnerable due to their higher inhalation rates relative to body weight. Sensitivity analysis pinpointed inhalation rate, exposure duration, and exposure frequency as the dominant parameters driving risk levels, indicating these pathways should be prioritized in mitigation strategies. These results emphasize the importance of improving environmental oversight and implementing stricter emission controls in mining areas to reduce airborne metal pollutants and protect public health.

Furthermore, the study underscores the utility of Monte Carlo simulation in health risk assessments, particularly in accounting for variability and uncertainty in exposure parameters. By providing a probabilistic framework, the approach enhances the reliability of risk estimates and supports more informed decision-making. The findings advocate for the inclusion of such advanced methodologies in environmental health assessments, especially in industrial regions with complex pollutant profiles. To build upon this research, future studies should consider assessing carcinogenic risks and cumulative effects from multiple contaminants, which would offer a more holistic understanding of long-term health implications and inform comprehensive regulatory policies.

6. Declarations

6.1. Author Contributions

Conceptualization, S.W.; methodology, S.W. and A.M.; software, A.M.; validation, B.; formal analysis, S.W. and A.M.; investigation, S.W. and A.B.B.; data curation, S.W. and L.M.S.; writing—original draft preparation, S.W. and A.M.; writing—review and editing, S.W., N.N.N., and LMS.; visualization, S.W. and A.B.B.; supervision, A.M. and B.; project administration, S.W. and B. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Acknowledgments

We appreciate all participants who kindly volunteered their time and thoughts to contribute to this research.

6.5. Institutional Review Board Statement

Ethics approval for this study was obtained from Hasanuddin University with financial support number: [22724093042].

6.6. Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

6.7. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7. References

[1] EPA. (1989). Risk assessment guidance for superfund. Human Health Evaluation Manual Part A, I(202), 1–89. Available online: https://www.epa.gov/risk/risk-assessment-guidance-superfund-rags-part (accessed on November 2025).

[2] WHO-IPCS. (2018). Guidance document on evaluating and expressing uncertainty in hazard characterization (2nd ed.). International Programme on Chemical Safety.

[3] Shokoohi, R., Khazaei, M., Karami, M., Seid-mohammadi, A., Khotanlou, H., Berijani, N., & Torkshavand, Z. (2021). Deterministic and probabilistic human health risk assessment approach of exposure to heavy metals in drinking water sources: A case study of a semi-arid region in the west of Iran. Journal of Environmental Health Science and Engineering, 19(1), 1047–1055. doi:10.1007/s40201-021-00671-4.

[4] Williams, R., Wilbur, S., Schnell, F. C., Wilson, J., Ogden, J. M., Wohlers, D. W., Hard, C., Kawa, M., & Citra, M. (2015). Toxicological profile for hexachlorobenzene. In ATSDR's Toxicological Profiles (p. 386). Available online: https://www.atsdr.cdc.gov/ToxProfiles/tp90.pdf (accessed on November 2025).

[5] Simonsen, L. O., Harbak, H., & Bennekou, P. (2012). Cobalt metabolism and toxicology: A brief update. Science of The Total Environment, 432, 210–215. doi:10.1016/j.scitotenv.2012.06.009.

[6] Jia, C. Y., Hao, W., Yin, L., Yuan, H., Han, F., & Yu, J. (2024). Occupational health risk assessment of exposure to major hazardous chemicals in copper and nickel smelting enterprises. Chinese Journal of Industrial Hygiene and Occupational Diseases, 42(10), 752-756. doi:10.3760/cma.j.cn121094-20240424-00188.

[7] Wu, Y., Li, G., Yang, Y., & An, T. (2019). Pollution evaluation and health risk assessment of airborne toxic metals in both indoors and outdoors of the Pearl River Delta, China. Environmental Research, 179, 108793. doi:10.1016/j.envres.2019.108793.

[8] Tunggala, S., Ken Amasita Saadjad, & Denny Robert Raintama. (2024). Komunikasi Partisipatif Untuk Mengurangi Dampak Lingkungan Pada Aktivitas Pertambangan di Morowali. Jurnal ISO: Jurnal Ilmu Sosial, Politik Dan Humaniora, 4(1), 12. doi:10.53697/iso.v4i1.1774.

[9] Wulandari, S., Mallongi, A., Budimawan, Birawida, A. B., Noor, N. N., & Alimin Maidin, M. (2024). Probabilistic Simulation and Sensitivity of Health Risks from Nickel and Cobalt Deposition Around the Mine. Pharmacognosy Journal, 16(5), 1159–1163. doi:10.5530/pj.2024.16.189.

[10] Varmazyari, Z., Ghannadpour, S. S., & Katibeh, H. (2025). Determination of cobalt concentration using nonlinear regression and Monte Carlo simulation in Zafarghand Region, Isfahan. Iranian Journal of Earth Sciences, 17(1), 1–9. doi:10.57647/j.ijes.2025.1701.08.

[11] Wang, J., Wang, B., Zhao, Q., Cao, J., Xiao, X., Zhao, D., Chen, Z., & Wu, D. (2025). Sources analysis and risk assessment of heavy metals in soil in a polymetallic mining area in southeastern Hubei based on Monte Carlo simulation. Ecotoxicology and Environmental Safety, 290(117607). doi:10.1016/j.ecoenv.2024.117607.

[12] Konnunaho, J., Eilu, P., Törmänen, T., Karinen, T., Ranta, J.-P., Rasilainen, K., Nykänen, V., Pokki, J., & Dehaine, Q. (2023). A mining industry overview of cobalt in Finland: exploration, deposits and utilization. Geoenergy, 1(1). doi:10.1144/geoenergy2023-016.

[13] Dieu Souffit, G., Saïdou, Bobbo Modibo, O., Lepoire, D., & Tokonami, S. (2022). Risk Assessment of Exposure to Natural Radiation in Soil Using RESRAD-ONSITE and RESRAD-BIOTA in the Cobalt-Nickel Bearing Areas of Lomié in Eastern Cameroon. Radiation, 2(2), 177–192. doi:10.3390/radiation2020013.

[14] Shekoohiyan, S., & Mehrabi, F. (2024). Health risk assessment of heavy metals in precipitated dust in goldsmith workshops and simulation using Monte Carlo method. Case Studies in Chemical and Environmental Engineering, 10(100973). doi:10.1016/j.cscee.2024.100973.

[15] Sakan, S., Mihajlidi-Zelić, A., Sakan, N., Frančišković-Bilinski, S., Kodranov, I., & Đorđević, D. (2024). Potentially toxic elements in sediments near mines—a comprehensive approach for the assessment of pollution status and associated risk for the surface water environment. Environmental Science and Pollution Research, 31(11), 16613–16628. doi:10.1007/s11356-024-32178-4.

[16] Paul, M. B., Ankan, A. D., Deb, H., & Ahasan, M. M. (2023). A Monte Carlo simulation model to determine the effective concrete materials for fast neutron shielding. Radiation Physics and Chemistry, 202(110476). doi:10.1016/j.radphyschem.2022.110476.

[17] Li, C., Yan, J., Yao, J., Xie, R., Yu, H., Yu, W., Meng, Q., & Dong, P. (2025). Unveiling priority control toxic metal in cover soil of anti-seepage tailings ponds: Insights from multi-media and probabilistic risk model. Process Safety and Environmental Protection, 197(107034). doi:10.1016/j.psep.2025.107034.

[18] Mohammadpour, A., Abbasi, F., Shahsavani, E., & Kazemi, A. (2025). The impact of mining on the ecosystem of central Iran's Wetland: A probabilistic approach to assessing ecological risk. Environmental Technology and Innovation, 38(104131). doi:10.1016/j.eti.2025.104131.

[19] Saintilan, N. J., Ikenne, M., Bernasconi, S. M., Toma, J., Creaser, R. A., Souhassou, M., Allaz, J. M., Karfal, A., Maacha, L., & Spangenberg, J. E. (2023). The World's Highest-Grade Cobalt Mineralization at Bou Azzer Associated with Gondwana Supercontinent Breakup, Serpentinite and Kellwasser Hydrocarbon Source Rocks. American Journal of Science, 323, 1–20. doi:10.2475/001c.91400.

[20] Ou, R., Huang, H., He, X., Lin, S., Ou, D., Li, W., Qiu, J., & Wang, L. (2023). Ecotoxicology of Polymetallic Nodule Seabed Mining: The Effects of Cobalt and Nickel on Phytoplankton Growth and Pigment Concentration. Toxics, 11(12). doi:10.3390/toxics11121005.

[21] Mohammadi, A., Mansour, S. N., Najafi, M. L., Toolabi, A., Abdolahnejad, A., Faraji, M., & Miri, M. (2022). Probabilistic risk assessment of soil contamination related to agricultural and industrial activities. Environmental Research, 203(111837). doi:10.1016/j.envres.2021.111837.

[22] Thyssen, J. P. (2011). Nickel and cobalt allergy before and after nickel regulation – evaluation of a public health intervention. Contact Dermatitis, 65(s1), 1–68. Portico. doi:10.1111/j.1600-0536.2011.01957.x.

[23] Askari, M., Soleimani, H., Babakrpur Nalosi, K., Saeedi, R., Abolli, S., Ghani, M., Abtahi, M., & Alimohammadi, M. (2024). Bottled water safety evaluation: A comprehensive health risk assessment of oral exposure to heavy metals through deterministic and probabilistic approaches by Monte Carlo simulation. Food and Chemical Toxicology, 185(114492). doi:10.1016/j.fct.2024.114492.

[24] Ebrahimzadeh, G., Omer, A. K., Naderi, M., & Sharafi, K. (2024). Human health risk assessment of potentially toxic and essential elements in medicinal plants consumed in Zabol, Iran, using the Monte Carlo simulation method. Scientific Reports, 14(1). doi:10.1038/s41598-024-75159-w.

[25] Mirzaei, N., Kalteh, S., Zamani-Badi, H., Moradpour, H., Parmoozeh, Z., & Baziar, M. (2023). Estimating human health risks associated with heavy metal exposure from bottled water using Monte Carlo simulation. Heliyon, 9(10). doi:10.1016/j.heliyon.2023.e20647.

[26] Zhang, B., Su, Y., & Shah, S. Y. A. (2023). Uncertainty Evaluation of Soil Heavy Metal(loid) Pollution and Health Risk in Hunan Province: A Geographic Detector with Monte Carlo Simulation. Toxics, 11(12). doi:10.3390/toxics11121006.

[27] Panqing, Y., Abliz, A., Xiaoli, S., & Aisaiduli, H. (2023). Human health-risk assessment of heavy metal–contaminated soil based on Monte Carlo simulation. Scientific Reports, 13(1). doi:10.1038/s41598-023-33986-3.

[28] Abedi, A. samad, Hoseini, H., Mohammadi-Nasrabadi, F., Rostami, N., & Esfarjani, F. (2023). Consumer health risk assessment of Arsenic and Mercury in hen eggs through Monte Carlo simulations. BMC Public Health, 23(1). doi:10.1186/s12889-023-16223-4.

[29] Orosun, M. M. (2021). Assessment of arsenic and its associated health risks due to mining activities in parts of North-central Nigeria: Probabilistic approach using Monte Carlo. Journal of Hazardous Materials, 412(125262). doi:10.1016/j.jhazmat.2021.125262.

[30] Rezayani, N., Mirmohammadi, M., & Mehrdadi, N. (2022). Determination of Selected Heavy Metals in Air Samples and Human Health Risk Assessment in Tehran City, Iran. Iranian Journal of Chemistry and Chemical Engineering, 41(8), 2674–2692. doi:10.30492/IJCCE.2022.139867.4429.

[31] Gu, X., Wang, Z., Wang, J., Ouyang, W., Wang, B., Xin, M., Lian, M., Lu, S., Lin, C., He, M., & Liu, X. (2022). Sources, trophodynamics, contamination and risk assessment of toxic metals in a coastal ecosystem by using a receptor model and Monte Carlo simulation. Journal of Hazardous Materials, 424(127482). doi:10.1016/j.jhazmat.2021.127482.

[32] Gaurav, V. K., & Sharma, C. (2020). Estimating health risks in metal contaminated land for sustainable agriculture in peri-urban industrial areas using Monte Carlo probabilistic approach. Sustainable Computing: Informatics and Systems, 28, 100310. doi:10.1016/j.suscom.2019.01.012.

[33] Mallongi, A., Rauf, A. U., Daud, A., Hatta, M., Al-Madhoun, W., Amiruddin, R., Stang, S., Wahyu, A., & Astuti, R. D. P. (2022). Health risk assessment of potentially toxic elements in Maros karst groundwater: a Monte Carlo simulation approach. Geomatics, Natural Hazards and Risk, 13(1), 338–363. doi:10.1080/19475705.2022.2027528.

[34] Shekoohiyan, S., Mahdavianpour, M., & Aghayani, E. (2023). Risk assessment and modeling of heavy metals in universal and local types of tobaccos. International Journal of Environmental Analytical Chemistry, 103(13), 2965–2980. doi:10.1080/03067319.2021.1900151.

[35] Zang, F., Wang, S., Nan, Z., Ma, J., Zhang, Q., Chen, Y., & Li, Y. (2017). Accumulation, spatio-temporal distribution, and risk assessment of heavy metals in the soil-corn system around a polymetallic mining area from the Loess Plateau, northwest China. Geoderma, 305, 188–196. doi:10.1016/j.geoderma.2017.06.008

[36] Chen, X., Ward, T. J., Sarkar, C., Ho, K. F., & Webster, C. (2022). Health risks of adults in Hong Kong related to inhalation of particle-bound heavy metal(loid)s. Air Quality, Atmosphere and Health, 15(4), 691–706. doi:10.1007/s11869-021-01115-6.

[37] Karimian, S., Shekoohiyan, S., & Moussavi, G. (2021). Health and ecological risk assessment and simulation of heavy metal-contaminated soil of Tehran landfill. RSC Advances, 11(14), 8080–8095. doi:10.1039/d0ra08833a.

[38] Chowdhury, T. A., Morshed, A. J. M., Islam, M. M. M., Islam, M. A., Chakraborty, D., & Azad, A. K. M. S. U. (2025). Heavy metal contamination, nutritional composition, and health risk assessment of biscuits: A Monte Carlo simulation approach. Food Chemistry Advances, 7(100944). doi:10.1016/j.focha.2025.100944.

[39] Soltanpour, Z., Rasoulzadeh, Y., & Mohammadian, Y. (2023). Occupational Exposure to Metal Fumes Among Iranian Welders: Systematic Review and Simulation-Based Health Risk Assessment. Biological Trace Element Research, 201(3), 1090–1100. doi:10.1007/s12011-022-03246-y.

[40] Sirinara, P., Chuersuwan, N., Pongkiatkul, P., Chanpiwat, P., & Jiamjarasrangsi, W. (2024). Quantifying the noncarcinogenic and carcinogenic risks resulting from the inhalation of PM2.5-bound metals: A multicity analysis and implications for public health. Ecotoxicology and Environmental Safety, 286(117198). doi:10.1016/j.ecoenv.2024.117198.

[41] Liu, S., Tian, H., Bai, X., Zhu, C., Wu, B., Luo, L., Hao, Y., Liu, W., Lin, S., Zhao, S., Wang, K., Liu, K., Gao, J., Zhang, Q., Zhang, K., Kan, H., Liu, Y., & Hao, J. (2021). Significant but Spatiotemporal-Heterogeneous Health Risks Caused by Airborne Exposure to Multiple Toxic Trace Elements in China. Environmental Science and Technology, 55(19), 12818–12830. doi:10.1021/acs.est.1c01775.

[42] Liu, Y., Yang, R., Chai, Y., & Wang, Y. (2025). Welding and burnishing dusts' exposure characteristics and health risk assessment in electromechanical processing workshop: Based on oxidation potential and EPA. Building and Environment, 279. doi:10.1016/j.buildenv.2025.112971.

[43] Pourhassan, B., Beigzadeh, Z., Nasirzadeh, N., & Karimi, A. (2024). Application of Multiple Occupational Health Risk Assessment Models for Metal Fumes in Welding Process. Biological Trace Element Research, 202(3), 811–823. doi:10.1007/s12011-023-03717-w.

[44] Sellamuthu, S., Saminathan, E., Veerappan, D., & Venkatraman, Y. (2025). Sporting footpaths and toxic dust: a risk-based assessment of urban, suburban, and rural exposure. International Journal of Environmental Health Research, 35(11), 3431–3458. doi:10.1080/09603123.2025.2487630.

[45] Hao, H., Li, P., Lv, Y., Chen, W., & Ge, D. (2022). Probabilistic health risk assessment for residents exposed to potentially toxic elements near typical mining areas in China. Environmental Science and Pollution Research, 29(39), 58791–58809. doi:10.1007/s11356-022-20015-5.

[46] Huang, W., Sun, W., Zhou, C., Long, K., & Zhang, Z. (2025). Probabilistic Health Risk Assessment and Grading Benchmark Estimation of Atmospheric PM2.5-Bound Heavy Metals in China. Archives of Environmental Contamination and Toxicology, 88(3), 377–396. doi:10.1007/s00244-025-01118-9.